# Visualizing Hydrodynamic Uncertainty in Operational Oil Spill Modeling

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## Abstract

A new method is presented to provide automatic sequencing of multiple hydrodynamic models and automated analysis of model forecast uncertainty on a Linux based multi-processor workstation. A Hydrodynamic and oil spill model Python (HyosPy) wrapper was developed to run a sequence of hydrodynamic models, link with an oil spill model, and visualize results. HyosPy completes the following steps automatically: (1) downloads wind and tide data (nowcast, forecast and historical); (2) converts data to hydrodynamic model input; (3) initializes a sequence of hydrodynamic models starting at predefined intervals on a multi-processor workstation. Each model starts from the latest observed data, so that the multiple models provide a range of forecast hydrodynamics with different initial and boundary conditions reflecting different forecast horizons. The GNOME oil spill model and a Runge-Kutta 4th order (RK4) particle transport tracer routine are applied for oil spill transport simulation. As an advanced visualization strategy, the Google Maps/Earth GIS API is employed. The HyosPy integrated system with wind and tide force is demonstrated by introducing an imaginary oil spill in Corpus Christi Bay. The model forecast uncertainty is estimated by the difference between forecasts in the sequenced model runs and quantified by using simple statistical processing. This research show that challenges in operational oil spill modeling can be met by leveraging existing models and web-visualization methods to provide tools for emergency managers.

## Methods

### HyosPy structure

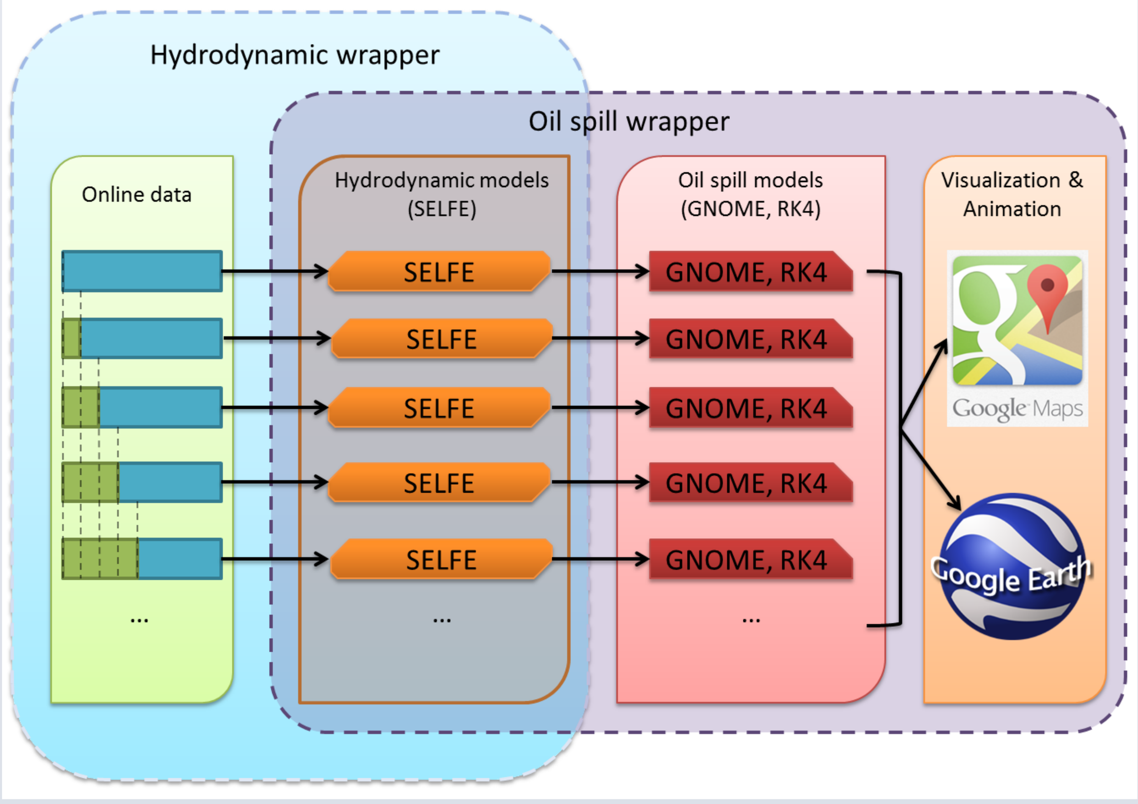


Figure 1. Python wrapper structure (Hou et al., 2014). In the *Online data* section, the dark blue strips reflect hindcast data, while the dark green ones reflect forecast data. The *Hydrodynamic wrapper* is able to initialize and run a custom series of hydrodynamic models (SELFE) automatically with a user-defined time interval in order to guarantee each SELFE is run with different initial conditions (hindcast/forecast data). The *Oil spill wrapper* functions to wrap the ensemble of different SELFE's outputs and translate them into the input format of the oil spill models. With multiple oil spill inputs with slightly different initial conditions, *Oil spill wrapper* can initiate and run multiple of oil spill models simultaneous, and visualize/animate different oil spill trajectories on 2D Google Maps GIS /3D Google Earth GIS.

## Methods (continued)

### Methods built in HyosPy

| Wrapper Name | Methods | Description |
|---|---|---|
| Hydro_wrapper | timer() | Create time interval |
| | change_param() | Change SELFE parameters |
| | change_data_time() | Custom data time period |
| | runSELFE() | Run multiple SELFE |
| Oilspill_wrapper | rk4() | Run RK4 model |
| | mul_GNOME_inputs() | Generate multiple GNOME's input |
| | run_mul_GNOME() | Run multiple GNOME |
| | GNOME_GM_visualization() | Visualize GNOME oil spill tracks on Google Map |
| | GNOME_GE_animation() | Animate GNOME oil spill tracks on Google Earth |

### Methods for estimating uncertainty

A simple uncertainty metric is the distance (eq. 1) between the predicted particle positions at each time step for the different simulations. The hydrodynamic forecast uncertainty is estimated by implementing simple statistical measurements mean distance (eq. 2) or root-mean-square distance (eq. 3) between corresponding particles compared across every simulation at a single time step based on the assumption that all models are equally likely (Hou, 2013).

$$L^k_{i:m,n} = \sqrt{(x^k_{i:m} - x^k_{i:n})^2 + (y^k_{i:m} - y^k_{i:n})^2} \qquad (1)$$

$$U^k_M = \frac{1}{2N_P(N_S-1)^2}\sum_{i=1}^{N_P}\sum_{m=1}^{N_S}\sum_{n=1}^{N_S} L^k_{i:m,n}(1-\delta_{mn}) \qquad (2)$$

$$U^k_R = \left\{\frac{1}{2N_P(N_S-1)^2}\sum_{i=1}^{N_P}\sum_{m=1}^{N_S}\sum_{n=1}^{N_S} (L^k_{i:m,n})^2(1-\delta_{mn})\right\}^{1/2} \qquad (3)$$

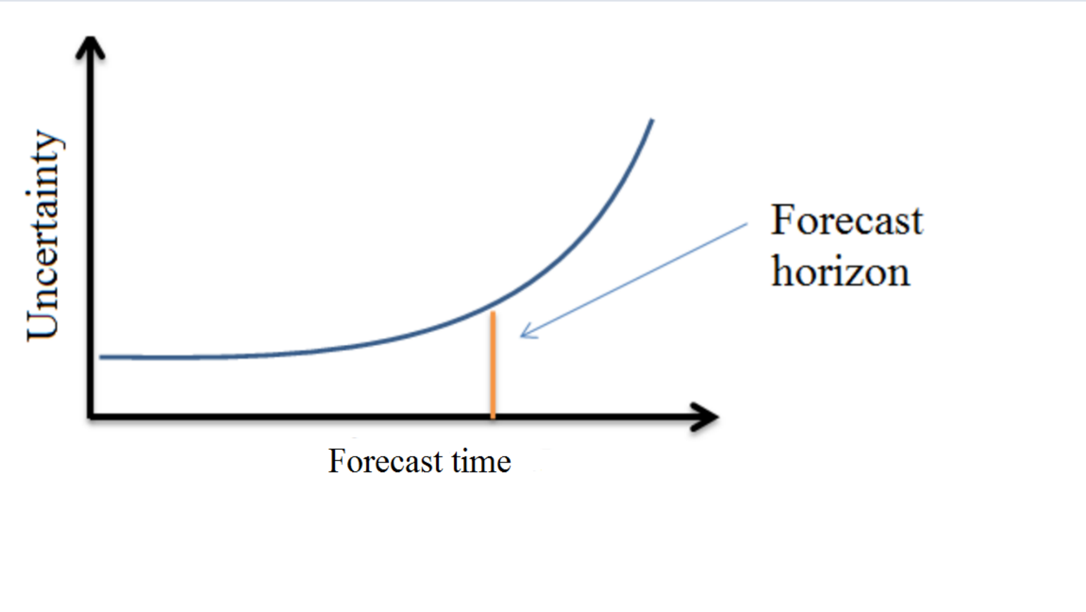


Figure 2. Expected hydrodynamic uncertainty in oil spill modeling (Hodges and Hou, 2013)

## Results

The following example shows a *HyosPy* simulation with wind, tide, and inflow force at Corpus Christi Bay for 48 hours (midnight 7/24/2013 to midnight 7/26/2013). Twelve hydrodynamic SELFE models are run at starting intervals of three hours.

| Model # | Start time | Hindcast hour | Forecast hour |
|---|---|---|---|
| 1 | 7/24 0:00 | 0 hour | 48 hours |
| 2 | 7/24 3:00 | 3 hours | 45 hours |
| 3 | 7/24 6:00 | 6 hours | 42 hours |
| … | … | … | … |
| 12 | 7/25 9:00 | 33 hours | 15 hours |

An imaginary oil spill is introduced at 0:00 7/24/2013 represented by 13 particles distributed about a center location. The multiple oil spill modeling based on the corresponding SELFE outputs were conducted using RK4 and GNOME. The results of the two models are almost the same. But the computation time of RK4 is much more longer than the GNOME. Thus, only results of the GNOME model are showing below:

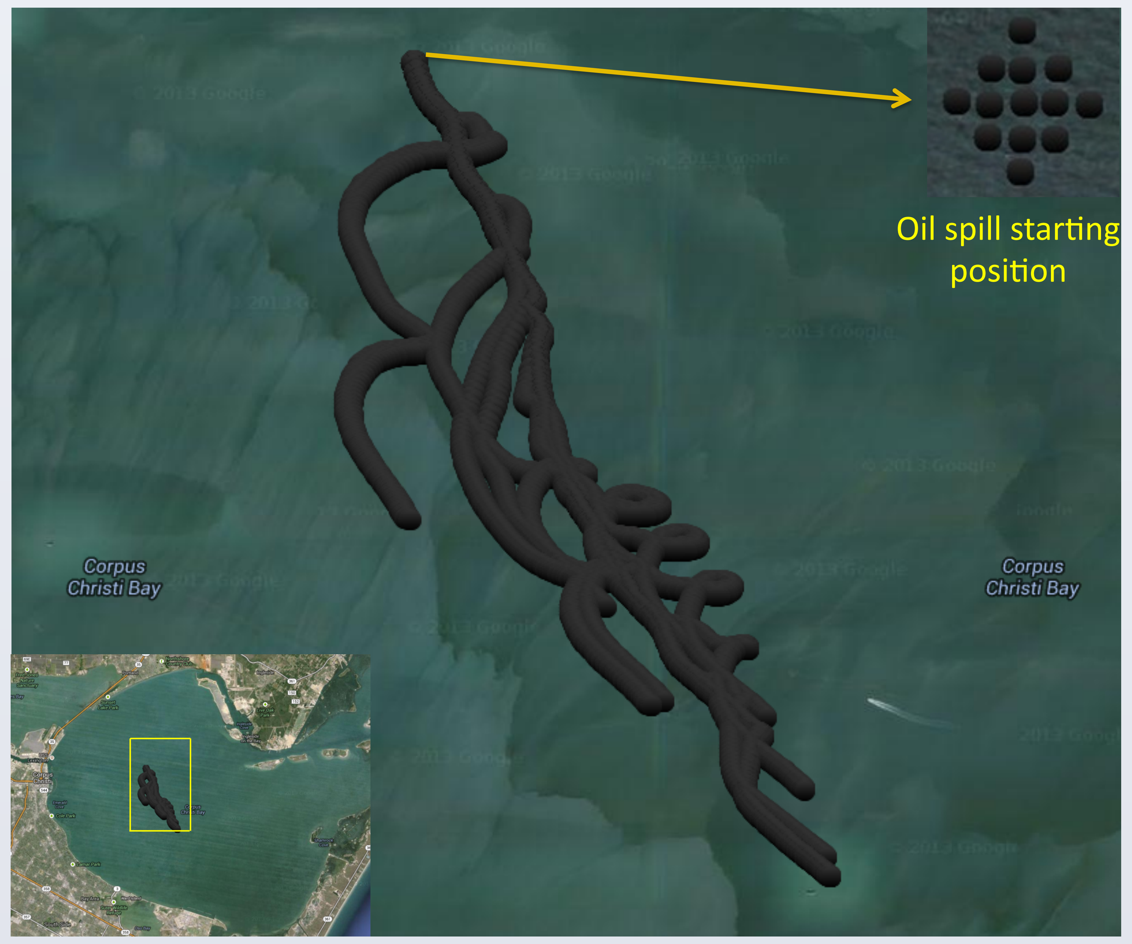


Figure 3. Twelve oil spill predictions (GNOME) visualized on Google Map (Hou and Hodges, 2014)

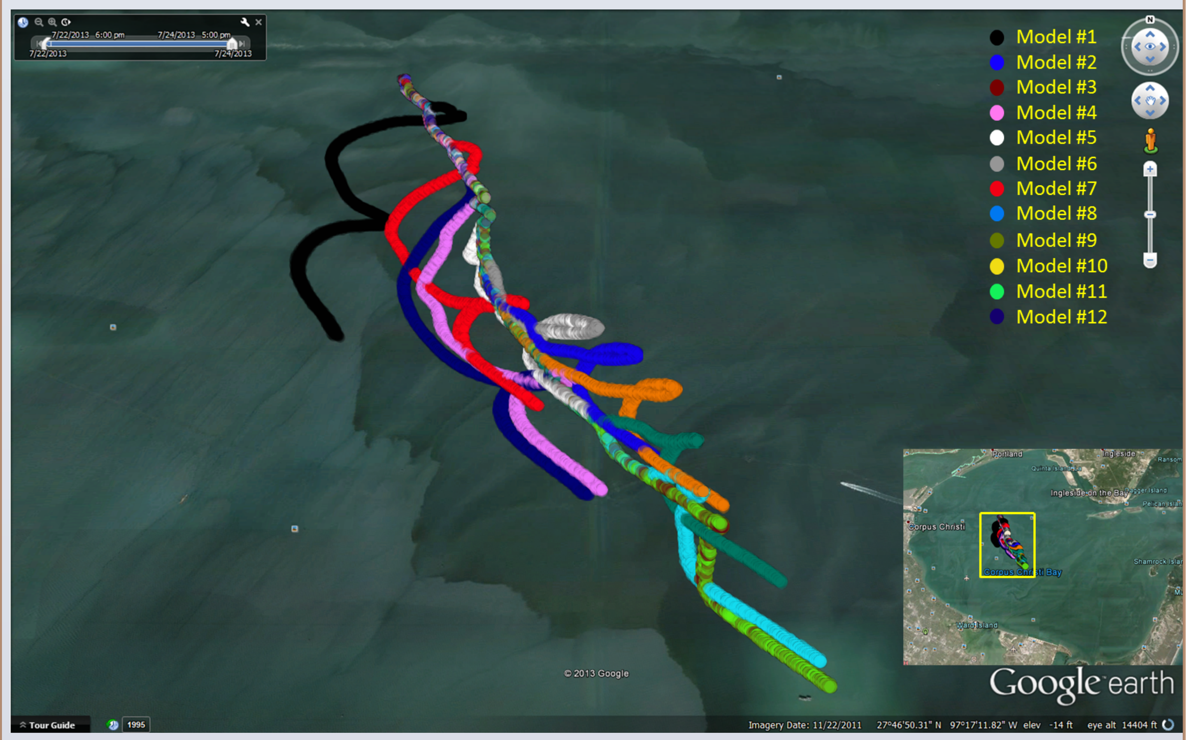


Figure 4. Twelve oil spill predictions (GNOME) animated on Google Earth (Hou and Hodges, 2014). The different color dots denote different oil spill predictions based on different combinations of wind/tide/inflow hindcast/ forecast. The whole movie about this particular event can be found here: http://www.youtube.com/watch?v=-5yNl0K6wJ4

## Results (continued)

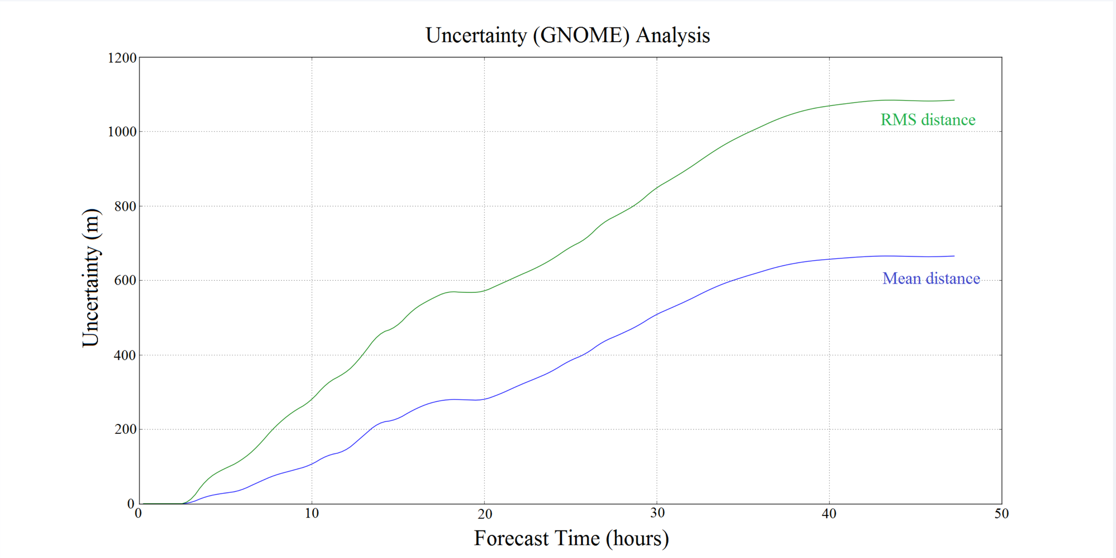


Figure 5. Hydrodynamic uncertainty in oil spill modeling (GNOME)

## Conclusions

We have developed a Hydrodynamic and oil spill model Python (HyosPy) to wrap a ensemble of hydrodynamic models (SELFE) with a same simulation time period but slightly different initial conditions in order to estimate the hydrodynamic uncertainty in oil spill modeling. The corresponding multiple oil spill model running can be easily conducted just by using a few HyosPy built-in methods. The results shows that HyosPy can automatically handle the increasingly complex operational modeling demands of which cannot be continuously and rapidly met by human modelers. The results also illustrate that the hydrodynamic uncertainty behaves as expected. More robust uncertainty analysis methods should be developed in the future.

## References

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